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Tree stem shapes derived from TLS data as an indicator for shallow landslides

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Abstract

Landslides or other forms of mass movement influence slope stability, and are known to have significant effects on vegetation patterns. Observation of such surface patterns may result in valuable information for understanding the kinematics of the landslide. In forested regions, tree growth anomaly is often served as an indicator of shallow landslide activity. Terrestrial laser scanning (TLS) is able to acquire accurate and dense 3D point cloud which provides the potential of reconstructing forest structure. In this study, we obtained high density TLS data in the northern Walgau in the federal state of Vorarlberg in Austria, where translational mass movement phenomenon exists in a forested region. A novel algorithm was developed to fast and robustly characterize single tree parameters (e.g. diameter at breast height (DBH), inclination angleof the stem and stem volume). Consequently, these tree parameters were successfully determined at single tree level. Field measurements were conducted in order to validate the results from the modelling algorithm. The root mean square error of DBHis 1.6 cm (4.9%). The average steminclination angle is 8.2°. The results of this study revealed that characterization of trees (i.e. inclination of the stems) can be used to indicate shallow landslide activities in forested regions. The quantification of tree parameters could also contribute to a better understanding of the interaction between landslides and trees.

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*Keywords:*Terrestrial laser scanning; landslide; stem detecton; cylinder fitting; stem curve; tree growth anomaly.

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1. Introduction

In mountain regions, slope instability is known to have significant effects on vegetation patterns[1].In the past decades, remote sensing techniques have been explored to map and assess landslides at regional scales[2, 3]. However, detailed above-ground vegetation characteristics on landside area are less investigated because of low density and quality of observed data. Terrestrial Laser Scanning (TLS) is able to acquire accurate and dense 3D point cloud of objects. It has been proven to be an effective tool in various environmental applications, e.g. forest research and management[4-8], monitoring in the geosciences, including landslide assessment[9], glacier monitoring[10, 11], and roughness quantification[12], but also in fields like deformation monitoring[13]and cultural heritage[14].The applicability of TLS technique provides the potential of reconstructing forest structure. Thereby, quantification of tree growth anomaly induced by landslides and soil creeping becomes feasible.

Tree growth anomaly is a phenomenon that is caused by soil movement in landslide regions[15]. However, so far in landslide researches,TLS is mainly used to monitor and quantify the displacements and deformations[16, 17]. Only a limited number of studies tried to characterize the tree growth anomalies caused by landslides[18, 19]. In Razaket al.[18], the authors evaluated the tree inclination angle using a skeleton method. However, their work involved enormousmanual delineation of single trees. Furthermore, only the inclination angle at the height of 1.3 m above ground was calculated.The lack of relevant studies calls for the development of automatic tree shape quantification approaches.

The current study focuses on the use of TLS data for quantifying tree growth anomaly in landslide-affected forests. The critical question is how to effectively detect and assess the trees in the region that is often characterized by steep terrain, dense understory, and complex stem shapes.Therefore, the objective of this paper is to present a novel algorithm for stem modellingand quantification in landslide-affected forest environments. We describe in this paper a random sample consensus (RANSAC) based robust stem reconstruction method, and a Frenet-Serret formulas based quantification method with application example for a landslide region in Austria. The purpose of this contribution is rather to discuss the general potential of using TLS data in assessing tree growth anomaly induced by shallow landslides,thus the main focus lies on the methodology, and not on geomorphological aspects.

In the following section 2 the study area and the used data are described, in section 3 the developed method is presented. Results and discussion are presented in section 4. Conclusions are given in section 5.

2. Study area and data

2.1. Study area

The study area is located in the northern Walgauin the federal state of Vorarlberg, Austria (Fig. 1), where several translational landslides exist. This small region is part of the covered study area of the project BioSLIDE (The influence of Biomass and its change on landSLIDEactivity)[20].The specific study site is inside a small forest located near the rupture surface of a shallow landslide, which is characterized by steep terrain with multi-layered canopy structure including dense understory, mixed forests, complex stem shapes and dead tree branches. Tree stems are overall curved due to the effects of soil movement. The dominating tree species are spruce, fir and European beech. Fig.2 shows the morphologic overview of the landslide in the investigated area. Water crop-outs from the mass material of several landslides indicate nearly saturated conditions of the landslide body.

2.2. Study data

The TLS measurement was conducted in October 2015, using a Riegl VZ-2000 scanner (Fig. 3a)[21].This scanner has a vertical view angle of 100° (+60°/-40°) and a full 360° horizontal view angle, with an effective measurement rate up to 400000 points per second (Table 1). Inside the forest, seven scans were performed (Fig. 1) in order to achieve a good coverage of all trees from different directions.Reflectors were placed on trees and used for the co-registration of various scans. Afterwards, the seven scans were registered using Riegl'sRiSCAN PRO software (http://www.riegl.com).The overall registration accuracy is ±7.5mm. The accuracy of orientation of individual scan is given in Table 2.Subsequently, all acquired data werefurthergeoreferenced to the coordinate system GK M28, which is the official system in the federal state of Vorarlberg, Austria, by geodetic survey methods using total station and GPS. Such transformation is helpful for future study, for example to comparethe TLS data or results with airborne laser scanning (ALS) data. The original point cloud contains more than 200 million points. An advanced sampling technique,namely leveled histogram sampling,was applied to reduce the point density[22]. A 7.5% sampling rate was chosen based on practical tests. Such a down sampling technique significantly reduces the further algorithm computation time, whereas at the same timeit is able to retain the quality of results.

In addition to the TLS measurements, the diameters at breast height (DBH) (height above ground is 1.3 m) of 27 trees were manually measured using a measuring tape and served as reference data. The average DBH in this study site resulted 32.8 cm and had a standard deviation of 14.3 cm.

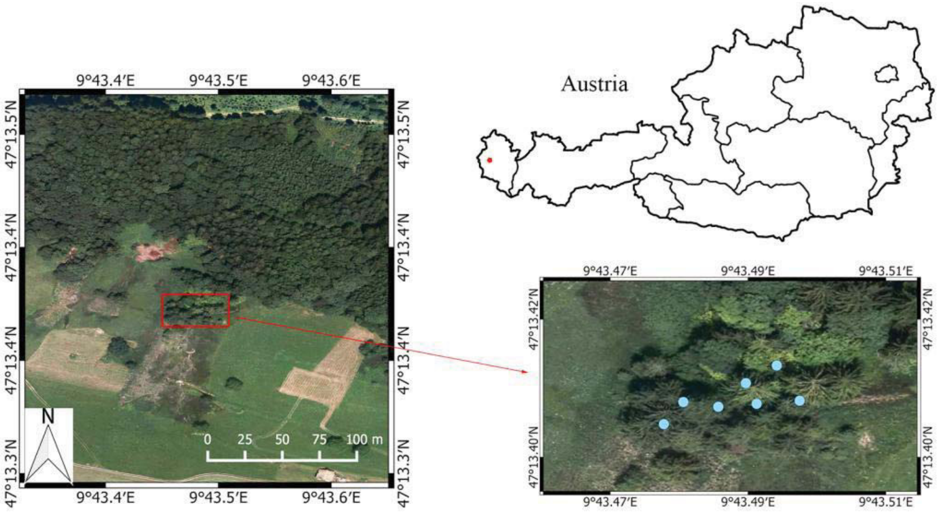

Fig. 1. Study region in the federal state of Vorarlberg, Austria. The red rectangle covers a small transection roughly equal to an area of 31 m × 19 m. The pale blue dots indicate the locations of seven TLS scans.

Table 1. Specifications of Riegl VZ-2000.

Specifications	Riegl VZ-2000
Max. vertical field of view (°)	100
Max. horizontal field of view (°)	360
Accuracy (mm) at 150 m range	8
Points per sec (max)	396000
Beam divergence (mrad)	0.3
Max resolution (°)	0.0015

Table 2. Accuracy of orientation of the scans.

Scan position	1	2	3	4	5	6	7
Number of tiepoints	5	5	6	4	5	4	4
Standard deviation (± mm)	4.8	12.4	7.8	7.2	8.1	4.5	5.4

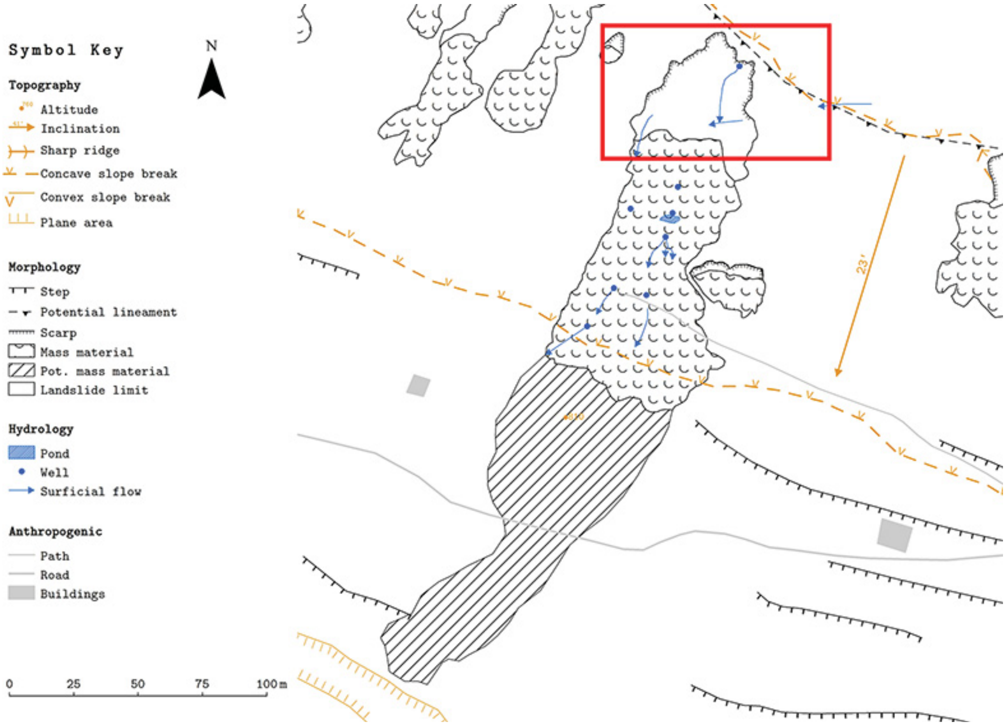

Fig. 2. Geomorphological map of study area. The red rectangle refers to the study site.

Fig. 3. (a) The scanner Riegl VZ-2000. (b) Field measurement. The white spheres are used for co-registration of seven scans.

3. Methods

3.1. Stem detection

The original point cloud contains data from all objectsin the field, such as terrain, low vegetation, tree stems, branches and leaves. In order to quantify tree stems shapes, it is essential to detect tree stems from the large amount of point cloud data. In a preparation step, the terrain is firstly modelled and removed. The derivation of the digital terrain model (DTM) is based on combinations of hierarchical interpolation and a robust filtering, basically similar to the mothed proposed by Kraus and Pfeifer [23], using the software package OPALS[24].The lowest points within 4 × 4 m² raster cells were used for a robust moving planes interpolation. For filling the gaps in the derived model a triangulated model is used, which is derived from the lowest points within 4 × 4 m² raster cells. The derived elevation model is used for normalizing the elevations of the original point cloud.

Afterwards, the critical question is how to effectively identify stem points. The normal vector method has been proven to be a promising approach[25]. Points on a vertical plane will have near horizontal normal vector, thus the z-components in normal vectors will be small compared with other points. In the forest, stems shape vertical surfaces. Therefore, stems points can be identified by calculating normal vectors. Lindberg et al.[26]andSimonse et al.[27]used the Hough transform to detect the stem locations by circle fitting. Such circle detection method works on either a slice of stem (e.g. 10 cm) at breast height or projected point clouds. Other methods such as spatial clustering[28] have also been explored.

Aforementioned methods in general utilize the spatial properties of tree stem points. These geometric attributes make detection feasible. However, our study aims at retrieving stem shapes in landslide-affected regions. Such forests are often characterized by dense understory, mixed forests and complex stem shapes. Therefore,common stem detection measurements in such forests are struggling withthe complexity of forest conditions. Especially, trees in landslide-affected forest often are disturbed by soil movement, which changed the wood formation mechanism[29]. The resulted stem shapes thus differ from vertical and the cross-section will haveanomalous shapes instead of circles.

In this study, our developed robust stem modeling algorithm only requires a rough estimation of stem locations. A method based on the combination of normal vectors and projection densities is proposed to delineate stem points. First of all, the normal vectors are calculated from locally approximated planes. Afterwards, all points are projected on the horizontal plane with 2 cm × 2 cm grids. The average absolute z component of the unit normal vectors in each grid cell is normalized by the amount of points in the grid (Fig. 4). A high amount of points as well as near horizontal normal vectors lead to small values. By applying a proper threshold, all grids that belong to tree stems can be identified. Furthermore, the selected grids are grouped by their locations, thus clustered as different stems. Each identified stem is enlarged by a 0.5 m × 0.5 m rectangular region to retain all surrounding points, because trees in landslide-affected regions are usually not vertical.

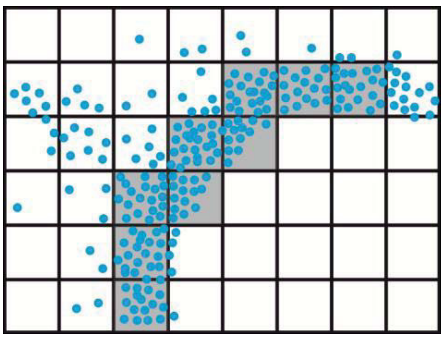

Fig. 4. 2D representation of simulated tree stem points that are projected onto horizontal plane. The gray grids are identified as part of stem using the method described in section 3.1.

3.2. Stem curve quantification

A RANSAC[30] based cylinder fitting strategy is applied to reconstruct the stems and retrieve the stem curves. Each stem is divided into 20 cm vertical sections, and the section that contains the most points is firstly fitted with a cylinder using RANSAC approach (Fig. 5). Subsequently, this cylinder is growing upwards and downwards by vertically shifting certain angles. The position of next cylinder can be found by adjusting the orientation and radius of the starting cylinder upwards or downwards. This procedure is continued until there are not enough points, i.e. reaching the bottom of the tree or not enough points exist in the upper crown. The result of stem fitting for each tree is a series of cylinders, and the connected central line is the retrieved stem curve, from which several parameters can be calculated, such as DBH, stem volume and stem inclination.

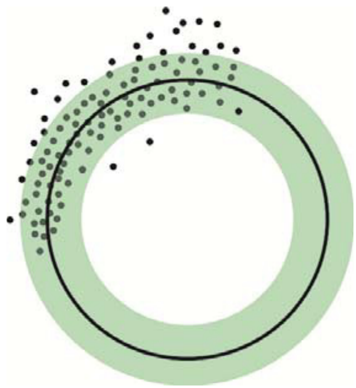

Fig. 5. Plan view of cylinder fitting. Black circle stands for the determined cylinder. Points within the green circular ring are identified as inliers.

The DBH and stem volume can be readily calculated from the fitted cylinders. The perimeter of the fitted cylinder at 1.3 m above ground is the DBH. The stem curve is a 3D curve consisting of various nodes at every 20 cm. In order to quantify the stem curve, we apply the Frenet-Serret formulas[31, 32]. In differential geometry, Frenet–Serretformulas describe the motion of a particle along the 3D curve. It consists of tree unit vectors, tangent (*T*), normal (*N*), and binormal (*B*), constituting an orthonormal frame, named Frenet–Serretframe.

$$\frac{dT}{ds} = \kappa N \tag{1}$$

$$\frac{dN}{ds} = -\kappa T + \tau B \tag{2}$$

$$\frac{dB}{ds} = -\tau N \tag{3}$$

Equations (1) - (3) are the Frenet–Serretformulas, where *d/ds* is the derivative with respect to arclength. Two intrinsicscalars κ and τ represent curvature and torsion, respectively.In addition, inclination angle can be calculated from normal vectors, as an extrinsic parameter. The quantification of stem curve allows us to examine how the stems are curved in vertical direction, and the corresponding height at which the stem exhibits the highest curvature can be determined. Fig. 6 shows an example of quantifying stem shapes using Frenet–Serretformulas. The inclination angle along the stem describes the deviation from vertical. The largest inclination is 16.9°, occurring in the lower part of the tree. Curvature represents the deviation from straight.

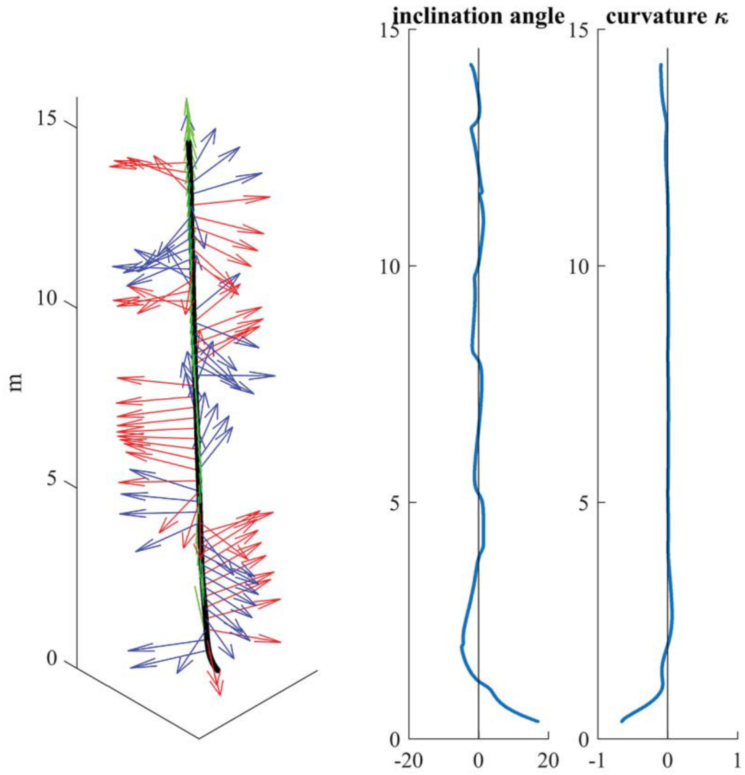

Fig. 6. Example of derived growth anomaly parameters for one tree using Frenet-Serret formulas.

4. Results and discussion

Stem shapes were successfully reconstructed and quantified with our novel algorithm. The root mean square error of reconstructed DBH in our study is 1.6 cm (4.9%compared to field reference data). The average inclination angle is 8.2 °, with the largest angle of 26.7°, while 1.3° is the smallest inclination angle. Large inclination always occurs at the lower part of the stem for all trees.All tree stems turn straight averagely at the height of 2.7 m above ground. Fig. 7 shows an overview of the results.

Accurate stem modelling is critical in terms of biomass estimation. Highly detailed biomass information can be integrated into physically-based models to further study the relation between slope stability and biomass[20]. Previous stem reconstruction works mainly deal with managed forestswhich are less complex than landslide-affected ones,or manually cleaned datasets. In addition, previous works focused on retrieving tree parameters such as location, DBH, tree height[6, 33, 34]. Stem curve and biomass estimation have also been explored using TLS[8, 25, 35], in which the whole stem was reconstructed either using cylinder fitting or circle fitting for various slices. Most of the approaches require an accurate delineation of stem points, thus the stem reconstruction can be feasibly conducted. Yet our RANSAC based stem reconstruction method does not require a fine delineation of stem points, and is robust with points from branches, leaves and other outliers. Such applicability is crucial when applying to trees grown in landslide-affected regions, because delineation of stem points can be difficult due to the complex field conditions. Our achieved accuracy of DBH is comparable or even better than previous studies [6, 8, 25, 27, 35-37], demonstrating the feasibility of our algorithm.

In addition, the characterization of tree growth anomalies is also crucial in the assessment of shallow landslide activities. Previous study[18] used a skeleton method to retrieve inclination angles, which involved a large amount of manual works for delineating single trees. However, to the best of our knowledge, no automatic stem shape quantification method has been exploited so far. Whereas our method works in a fully automatic manner. In this study, individual tree can be detected using a method combines the normal vectors and projection density. Further, we applied the Frenet-Serret formulas to quantify the motion of stem curve in 3D space. The derived parameters including inclination angle, curvature, torsion, and even orientation are valuable to assess the tree growth anomaly. Notably,our RANSAC based stem reconstruction and curve retrieval approach is robust with branches, leaves or noises in point clouds. Several parameters other than inclination angle can be assessed simultaneously by exploiting the Frenet-Serret formulas.In our study site, an average inclination angle of 8.2° is automatically estimated. Furthermore, our results show that bending and tilting of the tree stems occur usually at height very close to ground, whereas previous study[18] only quantified the inclination angle at 1.3 m above ground (i.e. the height of DBH).

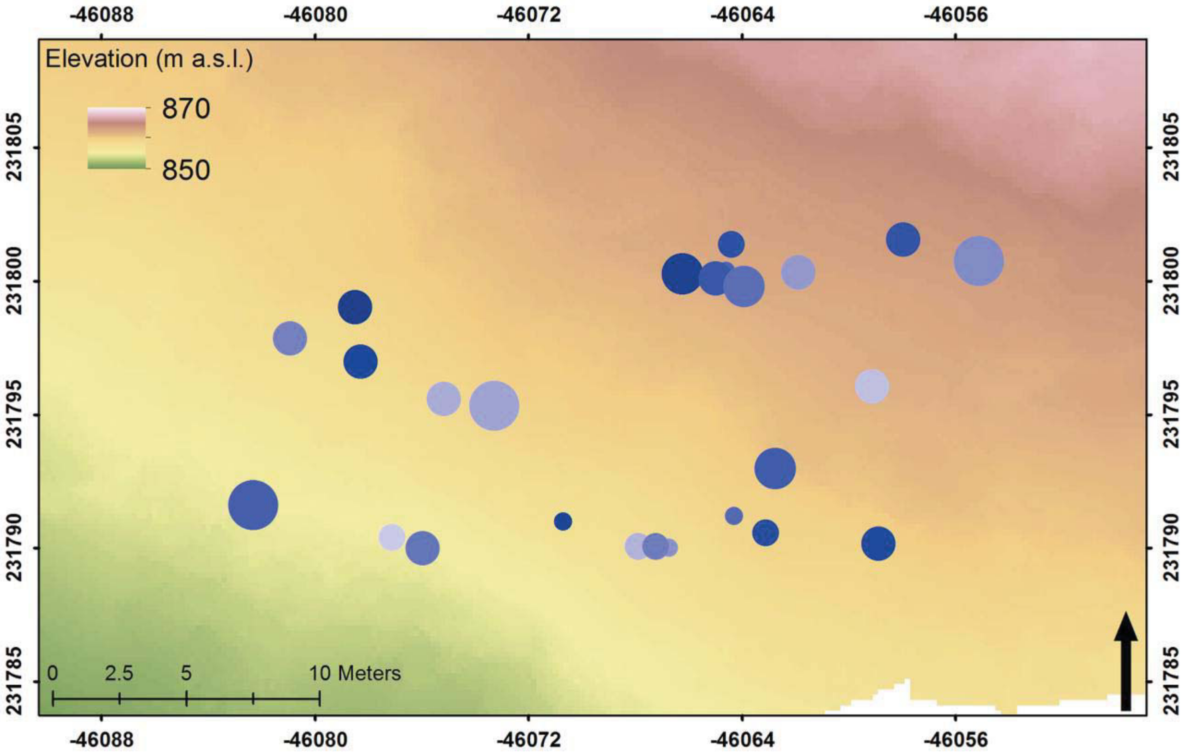

Fig. 7. Tree locations shown on a colored DTM. Coordinates are in GK M28. The size of circles stands for the DBH of stems, ranging from 9.2 cm to 61.2 cm. The color represents the inclination angles, ranging from 1.3° to 26.7 °. Colorlight blue refers to small angles.

As the focus of this contribution is mainly on discussing a method for automatically quantifying stem shapes, we did not pay close attention to the geomorphological implications related to landslides. Our preliminary statistical tests show that the inclination angles do not directly relate to neither the slope underneath the trees nor the DBH. However, in the form demonstrated here, our data sample size is too limited to interpret a geomorphological phenomenon. A next development step of our study is to enlarge the study site, potentially to cover trees on different parts of the landslide and in the vicinity of the landslide affected area.

5. Conclusion

In this study, we present a novel algorithm which is able to automatically detect, reconstruct and quantify tree stems. This method is specifically developed for trees in complex environments (i.e. canopy structure, steep terrain, amount of undergrowth, occlusions of the TLS point cloud, shaped tree stems). Tree parameters such as DBH, stem curve and volume can be retrieved with high accuracies. The root mean error of calculated DBH is 1.6 cm (4.9%) in our study. The accurate volume and biomass information derived can be integrated into physically-based models, thus helping the understanding of interaction between landslide and above ground vegetation. In addition, in landslide-affected forests, the advantage of TLSthat is able to acquire accurate and dense 3D point cloud of above ground vegetationcalls for stem shapes quantification approaches, and our study highlighted the potential of the methodology.The automatic approach assesses the inclination angle, curvature, and torsion along the tree stem. The average inclination angle is 8.2° in our study site. The derived indicators could quantify the tree growth anomaly induced by landslide, and contribute to a better understanding of the interaction between landslides and trees.

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